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Barriers to energy efficiency in industrial bottom-up energy demand models—A review

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ABSTRACT

The goal of this paper is to review bottom-up models for industrial energy demand with a particular focus on their capability to model barriers to the adoption of energy-efficient technologies. The integration of barriers into the models is an important prerequisite for a more detailed and realistic modeling of policies for energy efficiency. Particularly with the emergence of more and more varying policy instruments, it also becomes crucial for the models to take account of these policies as well as the barriers they address in a more realistic way.

Our review revealed that, despite the broadly evident existence of market failures and barriers for energy-efficient technologies, they are only partly and in a rather aggregated form considered in today's bottom-up models. The state-of-the-art bottom-up model is based on an explicit representation of the technology stock and considers the costs of energy efficiency options in detail. But with regard to barriers, most models only make use of an aggregated approach, like an adjusted discount rate. While some models do not even consider technology costs and energy prices, but instead use exogenous technology diffusion rates, other more advanced models took first steps towards considering barriers in more detail. The latter allows differentiation between multiple parameters that influence technology adoption. Still, even in the most advanced models, only a few of the observed barriers are explicitly considered.

At the same time, new approaches to considering barriers like uncertainty or the (slow) spread of information are being developed in other disciplines. We conclude the paper by summarizing promising ways to improve representation of barriers in bottom-up models.

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1. Introduction

The importance of improved energy efficiency for climate change mitigation, environmental protection in general, and reduction of fuel import dependency has frequently been shown [1]. As industry accounts for 36% of the global final energy demand, improving industrial energy efficiency should have high priority among policymakers. Furthermore, energy efficiency is also a matter of cost saving and competitiveness at the level of firms [2]. Consequently, knowledge about future industrial energy demand and the potential impact of energy efficiency policies is an important basis for policy design and investment decisions.

Energy demand models allow the impact of different technological developments on long-term energy consumption to be estimated. A key determinant of the market diffusion of new energy-efficient technologies is the technology adoption behavior of firms. A large body of literature has shown that investments in energy-efficient technologies are affected by barriers and market failures that often prevent the energy-efficient alternative from being chosen, although this would be cost-effective. Barriers can be very different in nature, varying from the availability of information or capacity within firms, to dealing with risk and how it is perceived, to firm internal processes or the availability of financial resources.

Still, current energy demand models work with fairly simple assumptions on the dynamics of technology diffusion, even if they are the type of bottom-up models[1] that are most often characterized by their detailed technology representation. In typical bottom-up models, technology adoption is considered as a strictly rational decision-making process, assuming perfect knowledge. Some models also consider barriers by assuming higher (implicit) discount rates for energy efficiency investments while others work with simple exogenous assumptions of the energy efficiency improvement [3]. While the first approach considerably overestimates investments in energy efficient technologies, the other approaches, i.e. the implicit discount rate and the exogenous assumptions, also lack a detailed understanding of the relevant barriers and their influence on technology adoption [4]. At the same time, a detailed consideration of the technology adoption process is indispensable for modeling energy efficiency policies that aim to overcome the barriers to accelerating technological change towards improved energy efficiency.

Indeed, including barriers and market failures into bottom-up energy demand models is frequently mentioned as an important step towards more "realistic" and reliable models and as a necessary step towards the more explicit modeling of policies [4–8]. Some promising first steps were taken towards this direction, and some approaches from other disciplines also exist that provide helpful insights into technology diffusion modeling.

Despite the growing attention for bottom-up models for industrial energy demand, there is as yet no overview focusing on the process of technology adoption and how it is considered in the models. Recent publications give an overview of particular issues of industrial energy demand modeling, but none of them focuses on the role of barriers in bottom-up models. Algehed et al. [9] for example compare modern bottom-up and top-down models, while Greening et al. [10] give an overview of the very broad range of approaches to model industrial energy demand, far beyond typical bottom-up models. Only Worrell et al. [4] exclusively focus on bottom-up models and their development needs, but they do not focus on technology adoption.

In this study we aim to fill this gap by providing an overview of the current status of bottom-up models for industrial energy demand with a particular focus on how these models consider barriers to the adoption of new technologies.

The paper is structured as follows. In the first part, we give a short overview of the barriers to energy efficiency and how they are related to the adoption of energy-efficient technologies by firms. We discuss both the empirical evidence as well as different ways of interpreting and classifying barriers which then provides the basis for the comparison of models.

In the second part, we review the current bottom-up models that aim at long-term forecasting of industrial energy demand. The focus lies on how they model the adoption of new technologies and the impact of barriers to energy efficiency. To answer this question, we analyze the more general modeling of technologies and technology stock (turnover). We also discuss whether the models have the potential to consider policies for energy efficiency. Modeling policies is the main reason for including more realistic firm behavior and barriers into the models.

2. Barriers to the adoption of energy-efficient technologies

Empirical evidence of barriers to the adoption of energy-efficient technologies has been widely reported in the literature. The following short overview of the main empirical findings and the different types of barriers will provide the basis for the analysis of the models in the second part.

The definition of barriers applied in this paper is based on Sorrel et al. [11]: barriers comprise all factors that hamper the adoption of cost-effective energy-efficient technologies or slow down their diffusion. They are regarded in contrast to a simple investment decision framework that only considers financial costs (investment costs and energy savings) and perfectly rational cost-minimizing agents with perfect foresight and perfect knowledge.

2.1. Evidence for barriers

Many studies have presented empirical evidence for the existence of barriers to energy efficiency. The studies found that many cost-effective options for energy efficiency improvements are not known to firms, or even if they are known and well defined, they are often not implemented – even when they show very low payback times of about a year. Several studies have concluded that – as financial factors alone cannot explain the non-adoption of energy efficient technologies – there must be "other" factors that determine these investments.

DeCanio [12] for example analyzed the influence of the financial and organizational characteristics of organizations on the payback time of projects undertaken in the frame of the US Green Light Program. A total of 3673 energy-efficient lighting projects recorded in the database of the Green Light program were analyzed. The results

[1] Sometimes also called end-use models or engineering-economic models.

of the regression analysis show that economic variables alone (like lighting hours, electricity prices, time lag or administrative cost) are not able to explain the experienced differences in payback times between organizations. On the contrary, DeCanio concluded that organizational and institutional factors strongly influence firms' investment decisions and that a large potential for energy-savings is still not realized, due to barriers.

An evaluation of the project database of the US Department of Energy's Industrial Assessment Center (IAC) program presents further evidence of the impact of barriers on investment decisions [13]. The database provided the results of over 10,000 assessments and over 70,000 single project recommendations. They found an implicit payback time threshold of 1.4 years. The analysis revealed further evidence for the hypothesis that simple investment criteria like payback time, initial implementation cost or annual energy savings do not suffice to explain the differences in investment behavior between plants and thus further decision determinants seem to exist. They also found that even recommended projects with a payback time close to zero were not implemented in 30% of the cases, which also indicates the existence of further investment determinants beyond simple profitability and risk criteria.

Harris [14] conducted a survey among 100 Australian firms that participated in the Commonwealth government's Enterprise Energy Audit Program (EEAP). They found that about 80% of the recommended efficiency improvements were implemented by firms. This high rate of implementation indicates that prior barriers existed that prevented the implementation of cost-effective efficiency improvements. The remaining 20% were mostly not realized because the rate of return was too low or the payback time too high.

In a similar way, several more studies give empirical evidence of the existence of market barriers to energy efficiency investment [15,16]. Also the often observed high rate of adoption of projects that were recommended by external energy audits indicates that cost-effective opportunities to improve energy efficiency are available in firms, but were neither analyzed nor implemented before the audits [14].

2.2. Classifying barriers

As shown in the literature, barriers are very heterogeneous in nature and were observed for all actors in the market. They are experienced differently among technology adopters and vary between technologies. As a consequence, many different ways to interpret and classify barriers emerged.

Many studies simply distinguish two main groups of barriers, namely market-related barriers and behavioral as well as organizational barriers [17,18]. Jaffe and Stavins [19] underline that many of the observed barriers are not market failures, but could well represent rational behavior at the firm level. Examples are dealing with uncertainty and risk by applying high discount rates. On the other side, examples for market failures are information asymmetries or principal agent dilemmas. The IPCC [20] proposes to distinguish four broad groups of barriers, namely, lack of information, limited availability of capital, lack of skilled personnel and a bundle of other barriers. These broad groups are further differentiated by Sorrell et al. [11] and Schleich [21] who classify barriers into six groups. They differentiate imperfect information, hidden costs, risk and uncertainty, split incentives, access to capital and bounded rationality. We apply the same definition for our analysis. Empirical evidence and examples are given below for each of these groups.

The importance of *imperfect information* as a barrier has often been empirically shown. The term comprises the knowledge about the availability of an energy-efficient technique, but also about its characteristics like costs and saving potentials as well as the actual energy consumption of the equipment in place. De Groot et al. [22] conducted a survey among Dutch firms and found that 30% of the companies interviewed were not, or only to a minor extent, aware of new existing energy-efficient technologies or practices.

Schleich [21] also groups the transaction costs for the search and information gathering process under the label of imperfect information. Transaction costs might be regarded as one reason for imperfect information. Hein and Blok [23] quantified transaction costs for the implementation of energy efficiency improvements in twelve plants in the Netherlands. They found transaction costs on the scale of 3–8% of the necessary investment. Of these, 2–6% can be attributed to information gathering costs, 1–2% to decision-making and less than 1% to monitoring activities. However, Ostertag [6] finds in her detailed analysis of transaction costs for energy-efficient electric motors that the transaction costs only marginally depend on the price of the motor and that their share generally decreases with increasing motor size.

Hidden costs prevent firms from undertaking energy efficiency projects although they are generally not quantified by firms and difficult to observe by outside observers. They may, for example, result from a poor quality of energy-efficient equipment or the hiring of staff. Although more a driver than a barrier, co-benefits beyond efficiency improvement are often observed for industrial energy-efficient techniques. They may result from waste reduction, reduced material consumption, lower maintenance needs, lower emissions or improved reliability and better product quality [24,25]. It may even occur that co-benefits are the main motive for the implementation of projects, while energy efficiency is more a side effect.

Access to capital is also frequently cited as an important barrier. It concerns external capital, but also the use of internal capital and the priority-setting among alternative investment projects. The survey by Harris [14] among Australian firms revealed that 35% of the non-realized but recommended efficiency projects were not implemented because they were assigned a lower priority than investment projects in the firms' core business. However, the survey also revealed a lower importance for the availability of finance as a barrier. Other studies found – slightly contradictory – a high importance for access to capital as a barrier. Examples are Anderson [13] who found that the cash flow was mentioned most frequently as a barrier. Accordingly, a survey among 50 Greek industrial firms [17] found that the barriers which were observed by most of the participating firms were "no access to capital" (76%), "high cost of implementation" (76%) and "low rate of return" (74%). Similar results were found by Rohdin et al. [15] who identified limited access to capital as the single most important barrier in the Swedish foundry industry.

Barriers related to *risk and uncertainty* cover a wide range from uncertainty about future energy prices or technology development to risk of production interruptions and impacts on product quality. In the Swedish pulp and paper industry, the technical risk of production disruption was identified as the single most important barrier [18]. For the Swedish foundry industry it was identified as the second most important barrier [15]. With relation to uncertainty, the irreversibility of investments is often mentioned as a relevant barrier [14].

Split incentives can hamper the adoption of energy-efficient technologies at very different phases in the diffusion process and between different market actors. This is illustrated in a case study by de Almeida [26] about the diffusion of high-efficient electric motors (HEM) in France. He observed split incentives between different market actors, but also between different units within a single firm. He underlines the finding that all market actors (motor manufactures, end-users, original equipment manufactures (OEMs)) are focused on motor price and reliability instead of life-cycle cost.

Particularly the OEMs do not demand energy-efficient motors because they mostly compete on price and reliability when selling pumps, fans, etc. As they do not pay for the motor's electricity bill, they have no interest in integrating HEM into their products. A lack of transparency and information about the actual efficiency of the motors even intensifies this barrier, as it does not allow the end-user to compare the efficiencies of alternative motors. Internal split incentives between different departments can even further worsen this situation.

Schleich and Gruber [27] analyzed a set of 2800 interviews with private and public organizations from the German service sector and found that the investor/user dilemma showed the highest significance as single barrier.

Bounded rationality is classified as a further barrier. However, it is not specific for energy efficiency. Simon [28] argues that observed business decision-making conforms better with the assumptions of bounded rationality than with the dominant economic theory of rational choice. Instead, many behavioral theories of the business firm assume "satisficing" rather than "optimizing" behavior. Consequently, decision makers base their decisions on rules of thumb or heuristics.

de Almeida [26] applied this concept to explain firms' investment in energy efficient motors. In the case of a broken motor, smaller firms especially do not have the capacity to compare alternative motor types. Their focus is on getting a new motor as quickly as possible, because even short production interruptions cost several times the motor price. As a consequence, they replace the broken motor with a new motor of the same brand and type. But even larger firms, who generally have a stock of replacement motors, mostly decide on the basis of motor prices instead of life cycle costs.

3. Modeling industrial energy demand

3.1. Typology of energy demand models

Energy models can be classified according to a variety of different characteristics like the modeling goal and scope or the methodological approach [29]. The following discussion will focus on models for energy demand forecasts and apply a classification based on their methodological concept.

Energy demand models are typically differentiated into two general groups, top-down and bottom-up models – representing the two main modeling philosophies. While the latter are rather built on an engineering philosophy, the former tends to represent the view of economists. The most often mentioned characteristic of bottom-up models is their detailed consideration of technologies, which means they allow modeling the impact of distinct, well defined technologies on the long-term development of energy consumption. With their technology explicitness, bottom-up models have the potential to model the effects of technology-oriented policies[2] [30].

In top-down models like computed general equilibrium (CGE) models, technologies are typically represented within aggregated production functions, which have lost any information on the type and the structure of the technologies they comprise. Technological change is traditionally considered as an autonomous energy efficiency improvement (AEEI) factor in these models. The AEEI represents a price-independent improvement of energy productivity. In recent years, improvements were made to incorporate technological change endogenously into top-down models as a price-induced, R&D-induced or learning-induced development [31]. But even when technical change is endogenous to the model, top-down models are not suited to analyze energy demand and its interaction with the evolution of the technological system. Top-down models have another field of application; they model interactions between the energy system and economic variables like employment or economic growth, whereas bottom-up models are restricted to the narrow system boundaries of the energy system [32,33].

However, the borders between top-down models and bottom-up models are not as clear as they may seem. In recent years, more and more modeling studies were conducted that integrated aspects of both approaches resulting in different types of hybrid models. They aim at overcoming weaknesses of a single approach by incorporating elements of the other approaches [34]. Barker et al. [35], for instance, use bottom-up estimations as exogenous input to a top-down framework to measure the economy-wide effects of climate change agreements in industry. The input parameters estimated by a bottom-up model assure transparent assumptions on the evolution of the technical system. Still, feedbacks from the macroeconomic world to the bottom-up model are not considered (compare [36]). Several approaches also exist where certain technologies are translated into constant-elasticity-of-substitution (CES) production functions in CGE models (e.g. [37–39]).

However, the technological detail that is modeled in top-down models is rather restricted. For example, Lutz et al. [38] distinguish between two alternative processes for steel production and Schumacher and Sands [39] distinguish 5 different processes. Thus, top-down models are not considered in the following analysis in order to allow for a maximum of comparability. Hybrid models are considered only if they contain a typical bottom-up part.

3.2. Review of bottom-up models

Bottom-up models are traditionally based on a detailed representation of energy end-uses like heating, lighting, mechanical energy or process heat [34]. The evolution of the end-uses and of their energy efficiency over time determines the future energy demand. Some bottom-up models explicitly distinguish between final energy and useful energy [40]. The demand for useful energy (e.g. heat, steam, mechanical energy, light) is projected for each end-use based on assumptions of main economic variables like industrial value added or production of energy-intensive products. The resulting amount of final energy is then calculated from the useful energy and the conversion efficiencies of the different technical systems. This distinction allows to separately considering effects resulting from the economic development or changes in industrial structure and effects resulting from the technical structure and energy efficiency. Thus bottom-up models have in common that they link energy demand forecasts to the technological structure of the energy system (Fig. 1).

With regard to technologies and the adoption and diffusion mechanisms, the models differ significantly. Also the extent to which barriers to energy efficiency are considered varies strongly among the models. Worrell et al. [4] identify three factors that influence technology adoption in most bottom-up models, regardless of how technologies are represented in the model. These are the availability of technologies, the financial costs[3] and operational decision rules.

3.2.1. Criteria for the comparison of models

The short overview on barriers already revealed a huge variety and showed that they differ between companies and sectors.

[2] We refer to technology-oriented policies as all kinds of rather technology specific policies like energy audits, information campaigns, standards and labels or technology subsidies. General energy taxes are not regarded as technology-oriented policy.

[3] Fixed and running costs of the investment as well aso saved energy costs.

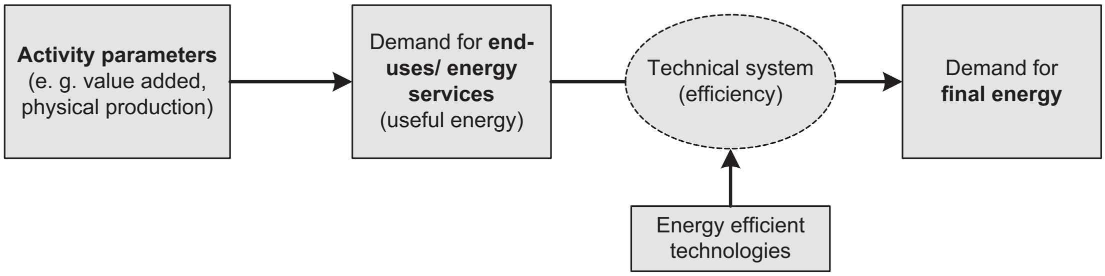

Fig. 1. Conceptual overview of typical bottom-up models.

As most of the discussed models show none or only a very simplified representation of barriers, the analysis of models will not directly build on the classes of barriers, but instead begin a step earlier. Thus, not only the barriers, but also the general capability of the models to take barriers into account is analyzed. The following model characteristics are used as criteria for the discussion below [4].

- Explicit *modeling of the technology stock* is regarded a prerequisite for a more detailed and realistic modeling of technology adoption and its determinants.
- *Financial costs*: Investment costs as well as energy costs are without doubt an important decision parameter for firms and thus their explicit consideration is a prerequisite for a detailed modeling of technology adoption and barriers.
- *Barriers* strongly influence technology adoption by firms. Only their consideration allows a realistic modeling of the technology stock.
- Modeling *policies* is the main goal of considering barriers in the models. The models differentiate in two aspects, the kind of policies they are able to consider and how the policies are linked to the technological structure and technology adoption.

We also consider models with a scope that goes beyond the industrial sector. However, when discussing the model characteristics only the industry part is considered and might differ in its structure, level of detail and assumptions on technical change from e.g. the simulation of the residential energy demand in the same model.

To discuss and compare the bottom-up models, we classify them into three main groups: accounting models, optimization models and simulation models. While optimization models optimize the choice of technology alternatives with regard to the total system costs to find the least-cost path, simulation models lack this system optimization perspective. They are very heterogeneous and some of them optimize from a firm perspective, while others do not optimize and instead consider other non-financial factors for the technology adoption decision. Accounting frameworks are less dynamic and do not consider energy prices, but mainly apply exogenous assumptions on the technical development [40]. Although we group the models into three classes, it should be clear that the borders are not as sharp and that some models show characteristics of more than one group. The models considered for our analysis are listed in Table 1.

3.2.2. Accounting models

Accounting models represent the first generation of bottom-up models and their first applications date back to the late 1970s [40]. They are generally characterized by exogenous definitions of many variables. They normally do not consider energy prices and thus do not explicitly model firm behavior with regard to the investment decision. The absence of prices as an energy demand determinant and the strong reliance on exogenous assumptions about technological change were recognized as major drawbacks of accounting models. Despite these shortcomings, they were frequently applied and present a powerful tool for the analysis of long-term energy demand, also because their simplicity and transparency is a huge advantage.

The MEDEE[4] model family is based on a long development tradition that started in the late 1970s and aimed to develop a new energy demand forecast tool to overcome the main shortcomings of the predominant econometric models [62,63]. Many different variants of the MEDEE model were developed, a commercialized and frequently used version of which is the MED-PRO model [43]. Energy efficiency improvements are exogenous to the model. For each product or sub-sector, an exogenous energy efficiency improvement rate is applied and determines final energy demand. MED-PRO was frequently used in energy demand forecasting studies, often for France [64]. A similar type of bottom-up model is MAED, which is derived from the MEDEE-2 model by simplifying the structure, but also by adding an extra module to calculate hourly electricity demand curves [44]. Technical change in MAED is considered on a highly aggregated level by exogenous changes in energy efficiency over time of an aggregated set of technologies [65]. Fuel switch is also exogenously defined.

For both models, MEDEE and MAED, neither a technology stock nor costs are explicitly taken into account. Consequently, barriers as well as the whole technology adoption process are only implicitly considered within the exogenously defined improvement of energy efficiency over time.

A flexible bottom-up modeling environment is the Long-Range Energy Alternative Planning System (LEAP).[5] In contrast to most of the other models discussed, LEAP is rather a framework that provides the essential tools for energy models, than a clearly defined model itself [45]. A typical application of the LEAP environment is presented by Wang et al. [46], who assessed the technological options and costs for GHG abatement in the Chinese iron and steel industry. Their model contains information on the performance, shares and costs of alternative iron and steel producing technologies. Policies are not explicitly modeled, but translated into an exogenous diffusion path of efficient technologies. This means for the investment decision that neither the capital stock nor the costs of the technologies are considered. In contrast to the study by Wang et al., however, LEAP also provides tools for technology stock modeling or cost assessments, resulting in models that would rather be grouped to the simulation models.

3.2.3. Optimization models

Optimization models were initially designed to model energy supply, but many of them were gradually extended to certain energy demand sectors or the entire energy demand side. Classical optimization models minimize the total system costs across all time

[4] Modèle d'Evaluation de la Demande en Energie.
[5] Developed by the Stockholm Environment Institute (SEI).

Table 1
Overview of the models considered.

	Reference	Sectors modeled	Methodological approach[a]
Accounting models			
MURE II	[41,42]	All demand sectors (EU)	Accounting framework
MED-PRO	[43]	All demand sectors	Accounting framework
MAED	[44]	All demand sectors	Accounting framework
LEAP[b]	[45,46]	Iron and steel	Accounting framework
Optimization models			
DNE21+	[47]	Iron and steel + energy supply	Partial-Equilibrium optimization
MARKAL	[48]	Industry + energy supply (global)	Partial-Equilibrium optimization
AIM/end-use	[49,50]	Iron and steel (Asia)	Partial-Equilibrium optimization
PRIMES	[51,52]	All demand and supply sectors (EU)	Partial-Equilibrium optimization
Simulation models			
CEF-NEMS	[7,53]	All demand and supply sectors (US)	Simulation
ENUSIM	[54]	Industry (UK)	Simulation
SAVE Production	[55]	Industry (NL)	Simulation
POLES	[56,57]	All demand and supply sectors (Global)	Econometric partial equilibrium
ISIndustry	[58]	Industry (EU)	Simulation/accounting
LIEF	[59]	Industry	Econometric simulation
CIMS	[60,61]	All demand and supply sectors (Canada)	Simulation

[a] This refers to the industrial sector module only.
[b] The description only refers to the application of LEAP by Wang et al., while Leap in general offers more functionality that would group it rather as a simulation model.

periods and assume equilibrium on energy markets, thus allowing for interactions between demand and supply. Mathematically, they are based on linear programming approaches.

A typical example of bottom-up optimization models is the MARKAL modeling framework, which has been developed by the IEA's Energy Technology System Analysis Programme (ETSAP) during the last 30 years [66]. Gielen and Taylor [48] describe the use of the MARKAL model for the IEA's Energy Technology Perspectives. The model minimizes the costs of the whole energy system for a chosen time period. Energy-saving options on the energy demand side compete with supply side options on the basis of their costs until the least-cost options are finally chosen. The optimization assumes perfect foresight[6] and perfect knowledge, which has two major implications. First, the future characteristics of technologies, energy prices, etc. are known and considered in the investment decision. And second, the minimization of costs over a time period prevents the occurrence of new "lock-ins", at least within the modeling timeframe. This approach is built on a social planner with perfect knowledge and implicitly assumes perfectly rational decision-making as well as perfect markets. The constraints for the technology adoption are the availability of new technology based on stock turnover, a "high" discount rate to account for uncertainty, as well as an exogenous limit for the diffusion speed of new technologies. Besides these three aspects, there are no further factors considered that influence technology adoption. Consequently, the analyses of environmental policies using MARKAL focus on financial policies like a carbon price or a quantitative emissions constraint in an emissions trading scheme. Several studies were conducted for chosen industrial branches like the iron and steel industry [67,68].

Oda et al. [47] used the global energy system model DN21+ to evaluate the effect of different greenhouse gas mitigation policies and the contribution from demand side mitigation in the iron and steel sector. They incorporated the global iron and steel sector into an energy system model to also capture feedbacks between energy supply and energy demand. The diffusion of new technologies is modeled as in most optimization models, by considering the technologies' capital stock, the lifetime and a discount rate (in this case 5%). The technology adoption then depends on the minimization of cumulative discounted costs of the whole energy system over the modeling period from 2000 to 2030. As in Gielen and Taylor [48], this approach assumes perfect knowledge and foresight throughout the whole modeling period and does not account for barriers.

An optimization model that was frequently applied in the Asian-Pacific region is the AIM/end-use model. It is part of the broader AIM (Asian Pacific Integrated Model) which aims to analyze climate policies, their costs and possible stabilization paths [49,69,70]. The AIM/end-use model considers technological change by alternative technologies that compete with each other on the basis of payback time or annualized lifecycle costs [49]. The model explicitly considers the technology stock and allows for new technologies to be employed in three cases: first, when old technologies retire or the energy service demand grows, second, by improving existing technologies and third by early replacement of an existing technology. Although the consideration of payback time can be regarded as an element of more realistic investment decision routines, the model is based on a cost-minimization algorithm that does not take barriers and further behavioral aspects into account [50].

Also PRIMES which is frequently used to establish long-term energy projections for the European Union (EU) [51,71], is based on an optimization algorithm that assures market clearing and thus assumes a partial equilibrium in the EU energy markets. However, PRIMES differs from other discussed optimization models in so far as it does not optimize a single economic function, but instead optimizes single sectors (e.g. the steel industry) following the rule of profit-maximization [52]. PRIMES explicitly considers barriers like perceived costs or risk premiums that hamper the diffusion of certain technologies. Risk is translated into a premium on the discount rate and differs between technologies and sectors. Other barriers are considered in a more aggregated way by allowing for alternative technology adoption rules. Technology specific policies can be integrated by lowering the perceived costs of certain technologies.

3.2.4. Simulation models

In contrast to optimization models, simulation models show a greater variety of different approaches and modeling philosophies, which makes it difficult to clearly define this type of models. In particular with regard to firms' technology adoption decision, the assumptions and implemented decision rules differ strongly. Many simulation models represent extensions of accounting models with a more detailed modeling of technology stock, technology adoption and firm behavior. We classify all models as simulation models that explicitly consider technologies and their stock and have an explicit

[6] SAGE is a version of the MARKAL model that explicitly does not assume perfect foresight [66].

technology adoption algorithm – as long as it is not the rule of minimized system costs which the optimization models assume.

A classical representative of simulation models is the NEMS (national energy modeling system) model as used for energy demand projections in the USA [7]. The technology adoption rule of NEMS-industry distinguishes two types of technologies, process and cross-cutting technologies [72].

For process technologies, efficiency improvements take place by either retrofitting the technology stock or by replacing old vintages with new state-of-the-art technologies according to a fixed annual replacement rate. Energy prices influence the annual rate by which the energy efficiency of the technology stock improves due to retrofitting. Thus, only the improvement of the current technology stock depends in part on the energy prices and thus reflects firm behavior that aims to counteract increasing energy prices by introducing energy efficiency measures. For the introduction of new technologies, it is argued that they are not introduced on the basis of energy efficiency considerations, but rather “autonomously”, taking other not explicitly defined factors into account.

For cross-cutting technologies, like compressed air or lighting, the stock model is extended by technology costs and the replacement of technology stock depends on a payback time threshold. The dominance of the payback time threshold as an investment criterion has also been empirically observed. However, other barriers are not considered.

ENUSIM is a bottom-up simulation model that exclusively focuses on energy demand in industry in the UK [54,73]. It applies the typical bottom-up approach and distinguishes between different energy end-uses that are projected based on exogenous assumptions of production output growth. ENUSIM explicitly models the technology stock by considering three different types of technologies, old (outdated) plants (I), present type of plants (II) and future plants (III) with the highest efficiency. Only plants of type III are allowed for capacity expansion. In addition to the plant database, the model also considers technology options that may be implemented to improve the plant efficiency by retrofitting. For the technology adoption rule, investment costs and behavioral factors are stated to be considered and the technology diffusion is based on the S-curve pattern. However, the diffusion curve for cost-effective technologies is exogenous input and thus all assumptions on barriers and investment behavior are only implicitly considered in the curve.

The approach followed by Daniëls and Van Dril [55] for the SAVE Production model considers risk, psychological effects of energy price changes and energy efficiency policies, as well as bounded rationality, besides the cost-effectiveness of the investment as decision factors. The approach is based on a technology stock model where a normal distribution around the average lifetime determines the share of the capacity that is to be replaced. Technologies are distinguished in “base-technologies” and “sub-technologies”. The replacement of sub-technologies depends on their own lifecycle, but also the lifecycle of the relevant base-technology. Risk is considered in the decision algorithm as a parameter that decreases the attractiveness of technologies. When the risk is higher, a larger internal rate of return is required for a positive investment decision. Non-financial barriers are considered by limiting the speed of the market diffusion. Also, psychological factors stemming from historical rises in energy prices and the stringency of policies are considered. The influence of the risk parameter and the factors for the psychological effects of policy and energy price changes are – due to data availability – mainly based on expert judgments. Thus the model is among the most advanced to consider barriers, but the empirical foundation of the parameters remains a challenge.

The CIMS (Canadian Integrated Modeling System) model is a further development of the former strictly bottom-up ISTUM model and covers all energy demand sectors as well as energy supply and economic feedbacks [74]. CIMS-industry explicitly models the development of the capital stock and differentiates between stock retirement, retrofit and purchase of new equipment due to production growth [61]. The decision-making algorithm is based on the classical algorithm of bottom-up models, but extended by three parameters representing behavioral realism and barriers. These are the heterogeneity of the market, the time preferences of the decision-maker and a factor for all other intangible costs and benefits. Markets with a high degree of heterogeneity observe less dominance of single technologies, even if they are significantly more cost-effective than others. The time preference of the decision-maker can be translated as the applied discount rate. The third parameter covers all remaining intangible costs and benefits that influence the decision-making. This parameter is not empirically derived, but adjusted when calibrating the model to observed market shares. The authors mention the huge amount of behavioral data needed for a technology explicit model and the difficulty of obtaining empirical data on preferences as two major drawbacks of their approach. To address these data needs, the authors combine the modeling work with surveys on consumer and firm preferences [30]. However, the CIMS model represents one of the most advanced approaches towards considering barriers and behavioral realism in bottom-up models.

In the following, three models are presented that use econometric estimations in simulation models to better capture firm behavior with respect to technology adoption.

POLES is a simulation model that extends the typical framework of end-use bottom-up models by using econometrically estimated relations to consider fuel elasticity and efficiency improvement on the demand side [57]. The model considers the energy demand and supply side, which are connected by energy markets, allowing for a partial equilibrium. Energy efficiency improvements take place by replacing retired stock with new more efficient plants. The efficiency of new capital stock and the energy carriers used are determined as an econometrically estimated function of short- and long-term price elasticity and an autonomous energy efficiency improvement factor. The considered price elasticities as well as the autonomous non-price related improvement allow for a certain consideration of barriers in technology adoption behavior, but at a rather aggregated level.

Davidsdottir and Ruth [75] used an econometric model to project energy use in the US pulp and paper industry that incorporates techno-economic data on capital vintages (studies were also conducted for the steel industry and the ethylene production [76]). They explicitly model the capacity expansion and the resulting energy efficiency improvement in new capital vintages. Energy efficiency improvement is considered through both the retirement of less efficient capital and the improvement of capital in place. It incorporates firm behavior by econometrically estimating key variables for the investment, like gross investment as a function of input prices and desired production volumes. However, the model aims to answer the questions, why new investments are made and what the impact of long capital lifetime on technical change is, but does not explicitly model the decision between alternative investments with differing energy efficiency. In other words, it is modeled “when” the investment decision in new capital takes place, but not which type of new capital is chosen.

The model ISIndustry is relatively young, it comprises the industrial sector and was mainly applied to EU countries [58]. It shows a huge technology detail and explicitly considers technology costs, while – in contrast to many other simulation models – it does not explicitly build a technology stock. The diffusion of energy-saving technologies, which is driving energy efficiency improvements, is to a large extent exogenous to the model. Costs are used to choose between alternative exogenous diffusion paths. Barriers are considered in an aggregated form by a combination of exogenously set dif-

Table 2
Overview of the explicit modeling of technology stock by model.

	Not explicitly considered	Explicit technology stock model	Technology replacement rules		
	Technical change mostly exogenous, often as aggregated efficiency improvement	Technology diffusion depends on lifetime and the age of current technologies.	Replacement after lifetime	Early replacement allowed	Retrofitting possible
Accounting models					
Mure II	X				
MED-PRO	X				
MAED	X				
LEAP	X	(X)	(X)	(X)	(X)
Optimization models					
DNE21+		X	X	X	X
MARKAL		X	X		
AIM/end-use		X	X	X	X
PRIMES		X	X	X	X
Simulation models					
CEF-NEMS		X	X	X	X
ENUSIM		X	X		X
SAVE Production		X	X		X
POLES		X	X		
ISIndustry	X				
LIEF	X				
CIMS		X	X		X

fusion paths and a premium on the discount rate. The model could be grouped as between accounting and simulation models, because on the one hand it shows a huge share of exogenous input parameters, but on the other hand it takes technology costs into account.

The LIEF[7] model made a particular effort to overcome the disadvantages of econometric approaches and traditional bottom-up modeling by combining both model types [59]. Thus, LIEF is able to determine main variables based on their historical trend and also to account for the firm behavior, while at the same time explicitly considering the potential of new technologies. Technologies are represented in the model as aggregated conservation supply curves that show the energy-saving potential and the related marginal costs, but that do not allow to identify single technologies. Thus, the technology stock is not explicitly considered. As in the other econometric models, barriers and behavior are implicitly considered in the historic trend, but not explicitly modeled.

3.3. Analysis and discussion

The following summary on the model review starts from the simplest concept and discusses distinct steps towards more complex models to finally arrive at models that would theoretically be able to model different kinds of policies based on a detailed representation of barriers. This discussion also gives an idea about how bottom-up models evolved over the past 30 years.

3.3.1. Technology stock

Although bottom-up models are mostly defined as being technology-explicit, they substantially differentiate in the level of detail and how they consider technologies (Table 2). Some of the early accounting type models, like MED-PRO or MEAD, consider technologies only as end-uses with a specific useful-energy demand and conversion efficiency. Often an entire production process (e.g. steel production) is reduced to one aggregated end-use. In these cases, the efficiency improves over time due to an exogenously given improvement rate and stock turnover is not explicitly modeled.

However, the technology stock and its turnover rate certainly have a huge impact on technology diffusion. Consequently, many models explicitly consider the technology stock and model energy demand by changes in the technology stock ([75,77], CIMS, MARKAL, DN21+, Save Production, POLES, etc.). The technology stock is at least characterized by technology vintages with differing specific energy consumption assuming that new technologies are more efficient. The decommissioning of old equipment and the introduction of new "state-of-the-art" plants improves energy efficiency in the technology stock. Virtually all models use age as the determining driver for stock turnover, although this may not be fully appropriate, as shown in a case study of the U.S. steel industry [78]. Some models also consider retrofitting of technologies in use (CIMS, NEMS-industry) or early (premature) replacement (NEMS, AIM/end-use, etc.). The technology stock approach already assures a certain reality with regard to technology diffusion, because the latter is bound to the lifetime of the technologies and their current stock. Thus, new technologies only diffuse when the capacity in the old stock is not sufficient – as a result of demand expansion or technology decommissioning.

3.3.2. Financial costs

All these changes in technology stock imply assumptions of the behavior of firms with regard to technology adoption. A central decision criterion in bottom-up models is the cost-effectiveness of the investment. Thus information about investment costs and saved energy costs are required. They are also a prerequisite to model price policies. Still, not all models consider (financial) costs. Among these are most of the accounting type models (MEDEE, MAED, MURE), but also more sophisticated models like for example the NEMS-industry model. NEMS-industry only explicitly considers costs for cross-cutting technologies, but not for industrial process technologies. Still, the stock turnover rate depends on the energy prices, so that a certain price sensitivity can be observed. Also some of the models working with econometric price elasticities do not explicitly consider investment costs (e.g. POLES, [75]). The reviewed optimization models all consider technology investment costs.

3.3.3. Barriers

Thus most simulation and optimization models explicitly consider the development of a technology stock and base the technology adoption on the cost-effectiveness of the investment – among other factors. When it comes to the adoption algorithm, i.e. firms' investment behavior and the impact of barriers, the mod-

[7] Long-term Industrial Energy Forecasting.

Table 3
Overview of the explicit consideration of barriers in bottom-up models.

	Not explicitly considered	Simple aggregated approach	Explicitly considered by type of barrier					
		Price elasticity, discount rate, all approaches that aggregate barriers	Imperfect information	Hidden costs (and benefits)	Access to capital	Risk and uncertainty	Split incentives	Bounded rationality
Accounting models								
Mure II	X							
MED-PRO	X							
MAED	X							
LEAP	X	(X)						
Optimization models								
DNE21+	X							
MARKAL		X						
AIM/end-use		X						
PRIMES		X				X		
Simulation models								
CEF-NEMS		X						
ENUSIM		X						
SAVE Production		X		X		X		
POLES		X						
ISIndustry		X						
LIEF		X						
CIMS		X		X				

els differ greatly from each other. While most models provide the ad-hoc option to consider high discount rates (to simulate stronger barriers), only individual models consider barriers more explicitly, and only to a certain extent (Table 3).

In general, the approaches followed by simulation models are much more varied, while the optimization models mainly follow the classical “minimization of total system costs” approach that considers only the financial costs of the investments and neglects e.g. transaction costs and information search costs (AIM/End-Use, DN21+, MARKAL). At best, optimization models represent barriers by higher discount rates (e.g. MARKAL) or by considering short payback periods as investment decision criterion (AIM/end-use). Recent developments aim to consider uncertainty about the development of future model variables like energy prices by introducing myopic agents (MARKAL-SAGE). As a consequence, cost-optimization can then not be conducted over all time periods and it may be possible for the “social planner” to choose a path that is not optimal in the long term, but ends with a lock-in situation.

Some of the simulation models present new approaches to improve the behavioral realism in the technology adoption algorithm (SAVE Production, CIMS). CIMS for example introduces three parameters, the heterogeneity of potential adopters, a discount rate (representing the time preference of the firm) and a factor capturing all other intangible costs and benefits. SAVE Production considers risk (as a discount rate), psychological effects stemming from energy price changes, as well as a policy factor that should represent the stringency of energy efficiency policies. But also PRIMES considers a risk premium and perceived costs depending on the type of technology.

Many bottom-up models were extended in recent years to include experience effects, thus falling investment costs with increasing deployment of a technology (e.g. MARKAL, CIMS). However, this effect is mostly considered for emerging energy supply technologies like renewable energies [79]. The consideration of experience curves for industrial energy-efficient technologies lags, partly due to rare empirical data and the difficulty of defining system boundaries around very integrated processes [80,81]. As long as experience curves are not properly integrated into energy demand models, the costs of reducing energy demand are overestimated and the potential of technological change to improve energy efficiency through the diffusion of new technologies is underestimated, in particular within an approach that considers rational cost optimization behavior. Thus, for an endogenous modeling of technology diffusion, experience curve effects are obligatory.

To conclude, none of the bottom-up models considers barriers in a comprehensive way. Instead, most of them consider barriers in an aggregated way, in the form of higher discount rates. Even the most advanced models in this respect (CIMS, SAVE Production, PRIMES) only consider a very small fraction of the barriers that were identified in the empirical literature Aspects considered in the models were higher discount rates (maybe used as a proxy for risk), payback time threshold as investment criterion, uncertainty about future development, heterogeneity among the adopters, psychological effects as a consequence of energy price increases, or cost reductions due to experience curve effects. Although the list seems long, it should be noted that this list combines all models and no single model considers more than three of these factors. Barriers that were found to be very important in the empirical literature, like no access to capital, lack of information and know-how, bounded rationality or principal agent dilemmas are not explicitly addressed in any of the models.

Also differences in the intensity of these barriers among firms, industrial sectors or technologies are only marginally considered. For example, NEMS-industry applies a higher discount rate to cross-cutting technologies than to process technologies, representing the presence of stronger barriers for cross-cutting technologies. Also CIMS estimates some of the barrier related parameters by technology.

3.3.4. Capability to model policies

The way technology adoption and diffusion is modeled and barriers are considered, restricts the types of policies that can be modeled. Two general groups of policies can be distinguished, price and non-price policies. Price policies can be energy or carbon taxes, they can in general be considered in all models that base the technology adoption on a classical investment decision by considering investment costs and saved energy costs (MARKAL, CIMS, DN21+, etc.). In particular, when the model philosophy is total cost mini-

Table 4
Overview of the explicit modeling of policies to improve energy efficiency.

	Policies as exogenous technology assumption	Price policies	Emission constraints	Technology specific policies		
	Policies exogenously considered in efficiency changes and/or technology diffusion	Taxes on energy or CO_2 emissions	Cap on the total annual emissions combined with trading of emission permits	Minimum standards for technologies	Subsidies and taxes on particular technologies	Policies addressing particular barriers (labeling, energy audits, contracting, low interest loans, etc.)
Accounting models						
Mure II	X			X		
MED-PRO	X			X		
MAED	X					
LEAP	X	(X)		X		
Optimization models						
DNE21+			X			
MARKAL		X	X			
AIM/end-use		X				
PRIMES		X	X	X	X	
Simulation models						
CEF-NEMS	(X)	(X)		X	(X)	
ENUSIM		X	X	X	X	
SAVE Production		X		X	X	(X)
POLES		X	X	n.a.	n.a.	
ISIndustry	X	X		X	X	
LIEF	X	X				
CIMS		X		X	X	

mization without considering barriers or bounded rationality, as in most bottom-up optimization models except PRIMES, simple investment calculation is sufficient to model price policies. However, as for simulation models, a realistic forecast is the goal, they need to consider barriers even to model price policies, otherwise they would end up with a too optimistic diffusion of efficient technologies. Thus, considering barriers is essential in order to arrive at a realistic price elasticity.

The situation is more complex for non-price policies, because these policies are as heterogeneous as the barriers they address. In many bottom-up models of the type of accounting frameworks, policies are typically modeled by exogenously adapting the diffusion rate of energy-efficient technologies or the energy efficiency improvement rates in comparison to a business-as-usual scenario (MED-PRO, MAED). A similar and very common ad-hoc approach to model energy efficiency policies aiming at barriers is the use of scenarios with a lower discount rate (MARKAL, ISIndustry, AIM/end-use). This is possible if barriers were considered in the form of a higher (implicit) discount rate in the baseline scenario. However, all of these ad-hoc approaches consider policies in a very aggregated and stylized way and none really allows representation of the characteristics of distinct policy design and intensity. Furthermore, choosing the "right" discount rate so that it represents a certain policy design and intensity is not practical.

First approaches that go beyond these ad-hoc policy modeling are the CIMS, PRIMES or the SAVE Production models. As these consider barriers in more detail, they should also be able to model policies that address these barriers more realistically. Although the representation of barriers is still rather aggregated, they already experience a strongly increasing demand for empirical data on firm preferences and behavior, which is particularly difficult to collect.

To conclude, most bottom-up models are not capable of explicitly considering distinct non-price policies for energy efficiency, mainly because they do not explicitly consider the barriers and the firm behavior that is addressed by the policies (Table 4). On the other side, bottom-up models are, due to their technological detail, theoretically very suitable for modeling technology-specific policies, like e.g. energy audits or information programs.

4. Conclusions and ways forward

While clear evidence of the existence of barriers has frequently been provided by different empirical studies, only a few bottom-up models consider barriers beyond the simple "discount rate approach". Even these "advanced" models (CIMS, SAVE Production) consider barriers in a rather stylized way, and only partly. They all have problems linking the model assumption to empirically assessed data. Heterogeneity between firms is only rarely considered and then rather stylized (CIMS, SVAE Production). The current state-of-the art bottom-up model explicitly models the technology stock and the costs of new technologies, while it shows only a simple representation of barriers by using an adapted discount rate. Thus, the rather exogenous and stylized consideration of barriers and technology diffusion sets restrictive limits for the modeling of energy efficiency policies.

However, promising approaches exist in the diffusion modeling literature [82] which bottom-up models could learn from [83]. These models come from disciplines like evolutionary modeling or agent-based modeling.

4.1. Uncertainty and spread of information

Various diffusion models present ways to model certain aspects of barriers like uncertainty and the spread of information. Jaffe and Stavins [84] propose an approach to model the diffusion of energy-efficient technologies while taking into account typical methods for technology diffusion modeling. The model considers both "epidemic" (gradual spread of a technology among adopters) as well as "probit" (heterogeneity among potential adopters) characteristics. Mulder [85] builds a diffusion model that is closely related to evolutionary economics and explicitly accounts for learning by using, uncertainty and heterogeneity. Another diffusion model considers irreversible investment and uncertainty about the availability of new (superior) technology [86,87]. These models show how the potential technology adopter postpones the investment due to a certain option value of waiting, although the investment would have been cost-effective.

A concrete first step towards considering aspects like increasing returns, uncertainty and heterogeneous agents with different attitudes towards risk in bottom-up optimization models has been presented by Ma et al. [88] by using a rather stylized diffusion model with two agents and three technologies.

4.2. Heterogeneity

The consideration of heterogeneity between firms and markets has been discussed as a critical aspect for more realistic bottom-up models. Different methodological approaches to improve the models are found in the literature. In general, probit models seem well suited, they derive the technology diffusion from differing characteristics of potential technology adopters [84]. Blok et al. [89], for example, considered heterogeneity in firms by implementing a distribution function of critical discount rates, which are used as an investment decision criterion. Also agent-based modeling may be a way forward to improve technology diffusion in bottom-up models and to explicitly account for heterogeneity between firms, as Schwarz and Ernst [90] showed for a diffusion model for water-saving technologies. They considered 12,000 potential technology users and classified them in typical consumer types. They linked the modeling work with empirical data from surveys and thus considered a wide set of heterogeneous technology adopters with differing attributes instead of one average adopter only.

4.3. Experience curve effects

The faster spread of the use of experience curves to bottom-up demand-side models is basically restricted by the low availability of empirical data on technology-specific learning rates. If this data were available, learning from energy supply-side modeling could help to integrate experience curve effects also in demand-side models [79].

4.4. Bottom-up model prototypes with the intention to consider barriers

While the diffusion modeling approaches provide methodologies to improve the modeling of heterogeneity, uncertainty with regard to energy prices or technology development, experience curve effects and spread of information, some important barriers are still not addressed. Among these are technical risk towards production disruptions, access to capital and investment priority-setting, lack of information on energy flow and relevant efficiency options, split incentives and bounded rationality. The following two modeling studies show how also many of these factors could be implemented in the bottom-up models. These models represent promising directions for future research activities.

A very comprehensive approach towards combining the literature on barriers with bottom-up models has been presented by Gillisen et al. [91]. They explicitly model firms' investment decisions by applying a three-phase decision model that breaks down the technology adoption into a knowledge phase, an economic evaluation phase and an implementation phase. All phases are influenced by barriers. Model calibration is done based on a survey among Dutch firms about their characteristics and the impact of barriers. The model considers barriers at a firm level by using barrier-specific variables like the degree of information sources, the importance of the environmental reputation or an uncertainty variable. Particularly the technology adoption module and the link between empirical data and model calibration shall be underlined and would be a good basis for further research.

Blok et al. [89] also propose a model that directly relates to the barriers discussion. They explicitly include 7 different types of barriers and differentiate between technologies. Examples of these barriers are the complexity of the technology, the financial situation of the industrial sector, threats to operational management by the implementation of a technique or the level of knowledge of the sector. This diffusion model is also linked to the ICARUS database on energy-saving technologies in the Netherlands.[8]

4.5. Conclusions

Current bottom-up models mostly represent barriers to the adoption of energy-efficient technologies in a very aggregated and simplified manner. Single models already undertook first steps for improvement, by considering heterogeneous markets, hidden costs or the firms' willingness-to-pay in addition to simple financial cost assessments. Furthermore, methodologies and approaches from other disciplines exist that could be used as a basis for improvement. Many can be found in the whole field of technology diffusion studies.

Still, the enormous technological heterogeneity in the industrial sector already poses challenges to the models [92]. With a comprehensive incorporation of barriers into the models, model handling and transparency will become even more of a challenge, as the amount of data needed will increase further. Consequently, also transparency with regard to assumptions and model routines will become more important when new and more diversified and complex modeling approaches are used. In general, data on firm behavior might be even more difficult to gather than technology characteristics data. Also here, some models showed first ideas to combine the modeling work with surveys explicitly designed for the model needs.

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